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Enhancing power system state estimation by incorporating equality constraints of voltage dependent loads and zero injections

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ABSTRACT

This paper presents a new state estimation (SE) method including equality constraints to model voltage dependent loads and zero injections. Formulation of conventional SE, assuming simple constant power model for the system's loads, is modified to incorporate voltage dependent load models. Assuming reliable load models and zero injections, it is analytically proved that modeling the equality constraints leads to better SE accuracy. To numerically validate the analytical findings, the proposed SE method is implemented on the IEEE 118-bus test system and the large-scale real-world Iran's power system, and its obtained results are compared with the results of conventional SE. Also, it is shown that considering voltage dependent load model in SE formulation leads to better performance of bad data detection. Moreover, it is illustrated that the accuracy of the proposed SE has low sensitivity to load model identification error.

1. Introduction

State estimation (SE) is a key module in energy management systems (EMS) for secure operation of electrical power systems. The accuracy of SE results and consequently other EMS applications, such as optimal power flow and security assessment, strongly depends on the implemented models for the system equipment besides the models' parameters. Loads of power systems are mostly represented by simple constant power model and thus voltage dependency of loads is usually ignored. Only near 16% of power systems worldwide consider the dependency of load on voltage in the security studies, e.g., contingency analysis, based on the results of SE in which the constant power load model is assumed [1].

The research works on state estimation can be categorized into two phases: developing SE solution algorithms and enhancing SE formulation. In the first phase, SE is mainly modeled as a weighted least squares (WLS) problem which is solved repeatedly based on the mathematical algorithms. There are several solution techniques, e.g., orthogonal factorization [2] and Cholesky decomposition [3], utilized in the literature for this purpose, that are different in numerical stability and computational efficiency. In the second phase, equality constraints for modeling zero injection buses, instead of artificially assigning high weights to them, are introduced in the WLS formulation to avoid the ill-conditioning problem [3]. A robust algorithm, which is a combination of symbolic optimal ordering and signed Cholesky factorization, is proposed in [4] and a reduced quasi-Newton method to solve the equality-constrained SE problem is used in [5]. Note that considering equality constraints in SE formulation might lead to divergence problem, when an equality constraint represents incorrect information. For instance, improper modeling of a load bus as a zero injection bus, due to incorrect recording the status of a load breaker, might happen in SE. To solve this problem, [6] has proposed a statistically and numerically robust estimator, combining Schweppe-type Huber GM estimator with orthogonal iteratively re-weighted least squares algorithm as well as the Van-Loan's method, to estimate the state and the transformer tap positions of a power system in the presence of bad leverage measurements and erroneous zero-injections. In the second phase, the researchers have tried to improve the performance of traditional SE formulation. For instance, [7] made a modification on WLS-based SE problem to consider the dependencies among measurements and the measurement noises were assumed to be correlated. Also, in [8,9], SE is solved based on information theory in which the decision making principle of minimum information loss is proposed to formulate SE. After introducing phasor measurement units (PMUs), many research works in the SE area have concentrated on incorporating the synchro-phasor measurements to improve the performance of SE modules like network

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observability [10], bad data detection [11] and parameter estimation [12].

The approach presented in this paper falls in the second category. This paper investigates the issue of incorporating equality constraints, pertaining to zero injections and voltage dependent load models, into the estimation process to improve the SE accuracy and the performance of bad data detection. The impact of considering equality constraints on the SE results is analytically and numerically evaluated in the paper. Additionally, to derive statistically sound conclusions, considering uncertainty of measurement errors, a Monte-Carlo simulation (MCS) based evaluation scheme incorporating probabilistic error criteria is presented.

The main contributions of this paper are as below:

1- Deriving an explicit expression for the sensitivity matrix of the state estimation problem with equality constraints (i.e., constrained weighted least squares problem).
2- Analytically evaluating the impact of equality constraints, pertaining to zero injections and voltage dependent load models, on the SE performance assuming reliable zero injections and load models.

It is noted that various load model identification methods have been presented in the literature. For instance, in [13–14], the load model parameters are determined using disturbance monitoring devices (e.g., digital fault recorders and power quality monitoring systems) that are capable of recording voltage and consumed power of substations. Today, with the advent of PMUs in power systems, the dispatch centres can receive the phase angles and magnitudes of voltages and currents with high sample rate at about 30–60 samples per second. In [15], the PMU data is used for determining the on-line load model parameters. Also, an unscented Kalman filter is presented in [16] to determine the parameters of voltage dependent load model in real-time using the SCADA measurements. The SCADA systems usually gather the measurements in the intervals of 2–5 s. Thus, to incorporate the voltage dependent load models into the SE formulation, the parameters of these models for load buses can be determined by the on-line load model identification methods mentioned above.

In addition, the load model parameters can be time varying in practical power systems due to, e.g., changing weather conditions and switching voltage control devices. Thus, an on-line load model identification method should be run prior to running the proposed SE method (e.g., in the period between two consecutive SE executions) to provide the required load model parameters. For instance, in [17] a robust recursive least squares method enhanced with variable forgetting factor and Huber M-estimator is proposed to identify the load model parameters using the voltage, active and reactive power measurements gathered through the SCADA system. This load model identification method can identify the on-line load model parameters in the normal operating conditions of power system and does not need to disturbance occurring.

The remaining parts of the paper are organized as follows. In Section 2, the conventional SE (CSE) is briefly reviewed. The proposed SE approach with equality constraints including zero injections and load models is presented in Section 3. The mathematical justification for the effectiveness of the proposed SE approach is given in Section 4. The numerical results obtained from the proposed SE for IEEE 118-bus test system and Iran's power system are presented in Section 5 and compared with the results of CSE. Finally, Section 6 concludes the paper.

2. Conventional state estimation (CSE)

CSE based on weighted least squares method is a nonlinear optimization problem as follows:

$$\min_x J(x) = [z-h(x)]^T\cdot R^{-1}\cdot[z-h(x)] \tag{1}$$

where x is the system state vector ($n\times 1$) including voltage angles and magnitudes, the vector z ($m\times 1$) consists of measurements in the snapshot and $h(x)$ is a vector of nonlinear functions ($m\times 1$), which relate the states x with the measurements z (e.g., power flow equations). Each telemetered measurement includes telemetry error and thus differs from its real value indicated by $h(\widetilde{x})$, where $\widetilde{x}$ is the true system state. Telemetry error e is mostly considered as random Gaussian noise with zero mean and variance σ_i^2 [3]. In (1), R represents covariance matrix of the measurements' errors. Thus, there is the following relation between the measured values (z), true values ($h(\widetilde{x})$) and corresponding noise vector (e):

$$z = h(\widetilde{x}) + e \tag{2}$$

To solve the nonlinear optimization problem of (1), Lagrange function and the optimality conditions of Kuhn-Tucker are applied and then Newton iterative approach is used to find the new estimated state ($\hat{x}^{k+1}$) at each step by adding $\hat{x}^k$ at the preceding step to:

$$\Delta x^{k+1} = G^{-1}_{(\hat{x}^k)}\cdot H^T_{(\hat{x}^k)}\cdot R^{-1}\cdot[z-h(\hat{x}^k)] \tag{3}$$

where $G_{(\hat{x}^k)} = H^T_{(\hat{x}^k)}\cdot R^{-1}\cdot H_{(\hat{x}^k)}$ is the gain matrix and H is the Jacobian matrix for the nonlinear functions $h(x)$, i.e., $H = \frac{\partial h(x)}{\partial x}$. The residual vector r ($m\times 1$) stating the difference between the measured and estimated values of the measurements is as follows:

$$z = h(\hat{x}) + r \tag{4}$$

where $\hat{x}$ represents estimated values of the states x. Also, the sensitivity matrix S ($m \times m$) relating the residual vector r and the measurement noise vector e is defined as:

$$r = S\cdot e \tag{5}$$

The sensitivity matrix S can be computed as below [3]:

$$S = I-H\cdot G^{-1}\cdot H^T\cdot R^{-1} \tag{6}$$

where I is identity matrix with appropriate dimensions. In constructing CSE formulation, the load models are assumed as constant power and voltage dependency of loads is ignored.

3. Proposed SE approach considering load models

A common model for power system loads is ZIP model [15–18], which is a combination of three physical components including constant impedance (Z), constant current (I), and constant power (P) loads. ZIP model is expressed as:

$$P_L(x) = P_o\cdot\left(a_P + b_P\cdot\left(\frac{V}{V_o}\right) + c_P\cdot\left(\frac{V}{V_o}\right)^2\right)\cdot(1 + K_P\cdot\Delta f) \tag{7}$$

$$Q_L(x) = Q_o\cdot\left(a_Q + b_Q\cdot(\frac{V}{V_o}) + c_Q\cdot\left(\frac{V}{V_o}\right)^2\right)\cdot(1 + K_Q\cdot\Delta f) \tag{8}$$

where $a_P + b_P + c_P = 1$, $a_Q + b_Q + c_Q = 1$, and $P_o(Q_o)$ represents the active (reactive) power at voltage V_o. The term $K\cdot\Delta f$ is usually disregarded in steady-state conditions as the amount of Δf (frequency deviation) is very small [18]. Since the voltages V are within the state vector x, P_L and Q_L in (7) and (8) are considered as the functions of x, i.e., $P_L(x)$ and $Q_L(x)$. Also, without loss of generality, it can be assumed that V_o is equal to 1 and so P_o and Q_o can be expressed as the consumed powers at the rated voltage. Thus, the following equations are yielded:

$$P_L(x) = P_o\cdot(a_P + b_P\cdot V + c_P\cdot V^2) \tag{9}$$

$$Q_L(x) = Q_o\cdot(a_Q + b_Q\cdot V + c_Q\cdot V^2) \tag{10}$$

As shown in (9) and (10), there are four unknown parameters in the ZIP-based static active load model (i.e., P_o,a_P,b_P,c_P) and reactive load model (i.e., Q_o,a_Q,b_Q,c_Q). However, considering $a_P + b_P + c_P = 1$ and $a_Q + b_Q + c_Q = 1$, three unknown parameters for each active and